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BEHAVIOR CLASSIFICATION AND OBJECT RANKING FROM MOVEMENT TRAJECTORIES IN TARGET REGIONS

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Orientadora: Profa. Dra. Vania Bogorny

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Mateus de Oliveira Barragana

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Esta Dissertação foi julgada aprovada para a obtenção do Título de "Mestre", e aprovada em sua forma final pelo Programa de Pós-Graduação em Ciência da Computação da Universidade Federal de Santa Catarina.

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Your thoughts become things!

Rhonda Byrne, The Secret

RESUMO

Vários métodos de mineração de dados têm sido propostos no últimos anos para descobrir diferentes tipos de padrões entre dois ou mais objetos em movimento. Apenas algumas obras identificam anomalias no comportamento de objetos em torno de determinadas regiões de interesse (ROI), tais como câmeras de vigilância, edifícios comerciais, etc, que podem ser de interesse para diversos domínios de aplicação, principalmente na área de segurança. Neste trabalho são definidos novos tipos de comportamento anômalo de objetos em movimento em relação à região de interesse, incluindo *surround*, *escape*, *return* e *avoidance*. Com base nesses tipos de comportamento anômalo é proposto: (i) um algoritmo para calcular estes comportamentos; (ii) um conjunto de funções para pesar o grau de comportamento anômalo de cada objeto em movimento; e (iii) uma classificaçao dos objetos em movimento de acordo com o grau de comportamento anômalo em relação a um conjunto de regiões. O método proposto é avaliado com dados reais de trajetórias e é mostrado que o trabalho relacionado mais próximo não detecta os comportamentos propostos e classifica os objetos considerando apenas um tipo de movimento anômalo.

Palavras-chave: Objetos em movimento, análise de trajetórias de objectos em movimento, objetos alvo, comportamentos anômalos, escape, surround, return, avoidance

ABSTRACT

Several data mining methods have been proposed in the last few years for discovering different types of patterns among two or more moving objects. Only a few works identify unusual behavior of objects around given Regions of Interest (ROI), such as surveillance cameras, commercial buildings, etc, that may be interesting for several application domains, mainly for security. In this thesis we define new types of unusual behavior of moving objects in relation to ROI, including surround, escape, return, and avoidance. Based on these types of unusual behavior we (i) present an algorithm to compute these behaviors, (ii) define a set of functions to weight the degree of unusual behavior of every moving object in the database, and (iii) rank the moving objects according to the degree of unusual behavior in relation to a set of ROIs. We evaluate the proposed method with real trajectory data and show that the closest work does not detect the proposed behaviors and ranks objects considering only one type of unusual movement.

Keywords: Moving objects, trajectory data analysis of moving objects, target object, unusual behaviors, escape, surround, return, avoidance

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1 INTRODUCTION AND MOTIVATION

The analysis of movement behavior of objects has been investigated for different purposes and explored in several domains such as videos (KO, 2008), (POPOOLA; WANG, 2012), transportation systems (CHEN et al., 2013), (BILJECKI; LEDOUX; OOSTEROM, 2013), (SHEN; LIU; SHANN, 2015), (PRELIPCEAN; GIDOFALVI; SUSILO, 2016), robotics (KLEINER; NEBEL et al., 2014), real-time systems (TOMáS-GABARRóN; EGEA-LóPEZ; GARCíA-HARO, 2013), (LIU; DU; YANG, 2005), (MAHJRI; DHRAIEF; BELGHITH, 2015), and others (BIUK-AGHAI et al., 2012). Different types of movement data have been used in these domains.

In GPS trajectory data analysis, which is the focus of this Master's thesis, the main goal has been on extracting patterns of trajectories *in relation to other trajectories* (GIANNOTTI et al., 2007),(SIQUEIRA; BOGORNY, 2011), (CARBONI; BOGORNY, 2014), (HUANG, 2015). On the other hand, the behavior of moving objects in relation to points of interest (POI), such as the work of (ALVARES et al., 2011), has not received much attention, but such discovery can reveal suspicious movements and unusual behaviors that are interesting for several application domains, mainly for security. For instance, a terrorist visits the place of future attack several times, and may stay during a long period watching the area. A thief or a killer may keep monitoring, moving around his/her target POI (e.g. a store, a bank, a house) for several times, before executing the crime, characterizing a *surround* behavior. A pedestrian that *avoids* a POI such as a security camera, or a car *escaping* from a blitz, may reveal suspicious and unusual behaviors in advance. By analyzing individual unusual behaviors of moving objects in relation to several POIs, such as the security cameras of a town, we are able not only to measure the behavior of a single object in relation to a set of POIs, but also to rank moving objects according to their unusual movements.

The discovery of behavior patterns in relation to points of interest was introduced by Alvares in (ALVARES et al., 2011), defining the *avoidance* behavior. The avoidance behavior is detected when a moving object explicitly avoids going towards a predefined fixed object, as shown in Figure 1. The region that involves the target object is called ROI (Region Of Interest), where the moving objects are able to notice the target object and either have a change of behavior or not. τ_1 in Figure 1 has a standard behavior, since the moving object crosses the target object o_1 keeping its original direction. On the other hand, τ_2

and τ_3 in Figure 1 have avoidance behavior, because they change their original direction inside the ROI in order to avoid the target object. The work of (ALVARES et al., 2011) detects only one type of behavior, the avoidance.

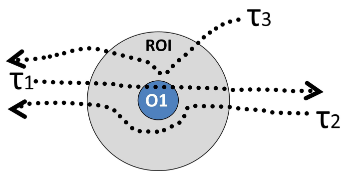

Figure 1 – Trajectory behavior examples.

In this Master's thesis we go one step forward in movement trajectory analysis, introducing the concept of *unusual behavior*, in order to identify different types of behaviors in relation to a target ROI. An *unusual behavior* is detected when the moving object has any *behavior change*, in terms of duration, speed or direction, from the standard behaviors dynamically observed at each target object and inside the ROI. More specifically, we introduce three new unusual behaviors: *surround*, *escape*, and *return*. Making use of these three new behaviors and an extension of the avoidance proposed by (ALVARES et al., 2011), we present a new algorithm to both compute these new behaviors and rank the moving objects in relation to a set of target objects, considering the unusual behavior recurrence cases.

To prove our algorithm efficiency, we perform three experiments with three different data sets. The first dataset is composed by trajectories that we simulated into an apartment complex in Florianópolis in order to have the method ground truth. The second experiment was performed with a dataset collected by Alvares to validate avoidance behavior. We used these trajectories in order to prove that our method is capable to find other unusual behaviors even in a specific data set. Last, we run an experiment with a massive trajectory data set collected by UFSC students and professors, which is used for general research. In this case, as we expect the students and professors have normal behavior, we simulated some unusual behavior. In summary, we make the following contributions:

- introduce three new types of unusual behaviors for moving objects: *surround*, *escape* and *return*;
- formalize the concepts of these patterns and the avoidance beha-

vior, which has not been formalized in (ALVARES et al., 2011);

- we dynamically infer the normal and unusual behaviors of moving objects in relation to every single ROI, since there is not a standard behavior that applies to all cases;
- define a measure to evaluate unusual local behavior, in relation to a single target object;
- define a measure to evaluate the global unusual behavior of every individual in relation to a set of target objects;
- propose an algorithm for both computing and ranking unusual behaviors in relation to a set of ROIs, considering *single* and *recurrent* unusual behaviors.

1.1 OBJECTIVE

The main goal of this Master's thesis is to analyze trajectories of moving objects, aiming to detect unusual behavior of parts of the trajectory in relation to a set of pre-defined static areas, to measure and to classify the unusual behaviors and to rank moving objects according to their unusual movement along their trajectories. In order to achieve the main goal, the following specific objectives are proposed:

1. Formally define all types of unusual behaviors;
2. Propose an algorithm to:
   (a) Detect and to classify unusual behaviors of moving objects in relation to every single ROI;
   (b) Rank moving objects according to their unusual behavior along the trajectory.

1.2 METHODOLOGY AND THESIS STRUCTURE

The methodology of this Master's thesis comprehends the following steps:

1. Research about the correlated works in unusual behavior analysis;

2. Formally define new types of unusual behaviors for moving objects: *surround*, *escape* and *return*, and the avoidance behavior, which has not been formalized in (ALVARES et al., 2011);

3. Propose a set of functions to measure local behavior and global behavior;

4. Propose and implement an algorithm to dynamically infer the normal behaviors of moving objects in relation to every single ROI, i.e., to identify the standard behavior of every single ROI, to detect and to classify unusual behaviors of moving objects in relation to every single ROI, to measure local unusual behavior in relation to every single target object, to measure the global unusual behavior of every individual in relation to a set of target objects and to rank moving objects according to their global unusual behavior;

5. Collect real trajectory data to perform the experiments. Data collection is made through GPS devices at a complex apartment and at UFSC, with the points captured in 1 second interval;

6. Perform experiments with different data sets of real trajectories;

7. Compare our results with the work of (ALVARES et al., 2011);

8. Analyze and discuss the parameters;

9. Write and publish a paper with QualisCC CAPES score of A or B;

10. Write the Master's thesis.

The reminder of the Master's thesis is organized as follows: Chapter 2 presents the related works. Chapter 3 presents the basic concepts to correctly understand the avoidance pattern and the bases for the new proposed behaviors. We introduce the new unusual behaviors in Chapter 4, and define an algorithm for ranking moving objects with unusual behavior in Chapter 5. In Chapter 6 we present the experiments to evaluate the proposal and a discussion about the method. Finally, in chapter 7 we conclude the thesis.

2 RELATED WORK

Moving objects pattern mining has been investigated in several areas, mainly in video surveillance. Some of these works are presented in Section 2.1. Section 2.2 summarizes the main works on GPS trajectory analysis to find unusual behavior, that are the closest to our method.

2.1 VIDEO ANALYSIS

Unusual behavior detection is a large research topic in video analysis (KO, 2008). Several works in this domain extract the trajectories of objects moving in the scene, and than propose different ways to analyze those trajectories together with other information extracted from the video images.

For instance, Lin in (LIN et al., 2009) proposes an object tracking algorithm that measures the frame similarity to classify people behavior by analyzing their trajectory patterns. Even though this work uses only trajectory data to identify people unusual behavior, the proposed method classifies the whole trajectory as usual or unusual, according to multiple discrimination rules that are described regarding previous knowledge of the camera coverage region. In our method a trajectory might have different kinds of unusual behavior in relation to a target object according to speed, trajectory time range and curve angles inside a region of interest, which would be a region around (outside) the camera. Besides, our "rules" are built without any previous knowledge of the region, only with information of trajectories that cross the target object.

In (LI et al., 2013a) another approach is proposed to detect human abnormal behavior using only trajectory information extracted from the video scene. A dictionary of normal trajectories is constructed based on collected trajectories with normal behaviors. The dictionary of normal behaviors is further divided into Route sets, which are equivalent to our standard sub-trajectories into ROI. Although there are similarities with our method, the abnormal behaviors are detected inside the fixed video scenario, which would be our target object, but not in relation to it. Indeed, the whole trajectory is classified as normal or abnormal, but the abnormality is not qualified and the trajectories are not ranked according to an abnormality degree.

(HOU et al., 2013) proposes an abnormal behavior recognition method that uses the features of trajectories extracted from the video, and regional optical flow to detect behaviors as fighting, destroying, damaging, etc. Such abnormal behaviors are often sudden, with short duration, but they cannot be identified only by trajectory analysis. So the optical flow that captures movement actions is used to detect normal and abnormal behaviors. The trajectory analysis is just used to remove normal trajectories in order to avoid high computational processing.

Chang in (CHANG et al., 2014) proposed a method to identify anomalous trajectories online. The method analyzes the distribution of moving patterns, where anomalous objects present sudden direction or position changes, while normal objects do not. The moving objects with a similar starting usually lead to the same set of ending location. Based on this observation, Chang proposes a rule-based mining algorithm to discover frequent traversal patterns from historical trajectories for a given surveillance video, identifies anomalous moving objects that are highly different and deviate from common traversal paths. The analysis of anomalous trajectories is in relation to other trajectories, and not in relation to a target object. Furthermore, there is neither abnormal behavior qualification nor moving object ranking.

(BURGHOUTS et al., 2014) proposes a system to detect specific behaviors such as a thief around cargo trucks. Some of the behaviors include fighting, loitering, and fiddling, among which, loitering is equivalent to our surround behavior, considering the truck as our target object and truck zone as our ROI. However, a lot of semantic information is used in the analysis, such as the zone where the trajectory starts, which zone the trajectory is moving, and which type of behavior is common in such zone. In our approach the ROI is a geospatial buffer around the target object and the standard behavior of every single region is dynamically calculated, based on the most common behaviors presented inside the ROI.

(WANG; WANG; CHEN, 2014) proposes a multi-camera method to extract trajectories and to look for rapid or irregular movements, such as running and abrupt change of velocity across the scene, which is very similar to our unusual behavior of escape. However, it is detected inside the scene (camera coverage region) and the anomaly analysis is based on SAX transition probability matrix of (KEOGH; LIN; FU, 2005). Our method uses trajectory features to analyze moving objects and we identify three other unusual behaviors based on trajectory speed, time range and curve angles.

In (NAM, 2015) another real-time method to detect people loitering in video scene of public areas is proposed. After locating and tracking the object, loitering behaviors are evaluated inside a ROI by comparing the movement time of the objects with context information about the public area. Despite the similarity of the loitering with our surround behavior, ROI is a bounding box in the video scene. In our approach ROI is a geospatial buffer around the target object and moving objects are evaluated against the movement time dynamically calculated with usual behaviors inside the ROI.

In vehicle traffic monitoring systems, unusual behavior detection is very useful and explored. For instance, in (BRUN et al., 2014) a graph based approach is proposed for detecting abnormal behaviors starting from the analysis of vehicles' trajectories. During the learning phase, the scene is partitioned into a certain number of zones depending on the density of trajectories crossing it. Each zone encodes one vertice of the graph and the probability to move from one zone to another encodes the edges. So, the scene is fully represented as a weighted and oriented graph. On the tests phase, a new trajectory can be considered as having normal behavior when the trajectory corresponds to a path of the graph crossed by a large amount of trajectories belonging to the training set, otherwise the new trajectory is identified as abnormal. The vertices of the graph can be considered as the target object and the abnormal behavior is detected when the trajectory does not achieve a minimum threshold of normal transitions among the target objects. However, no other features of the trajectory are used in the analysis besides the trajectory itself. Brun only classifies the trajectory as having or not abnormal behavior.

Another research topic in video analysis is abnormal behavior detection in crowded scenes. For example, (CHONG et al., 2014) presents a novel approach to model the spaiotemporal distribution of crowd motions and to discover anomalous events for individuals and for crowds. Firstly, the regions of interest (ROIs) are learned from historical trajectory sets. ROIs are a multinomial distribution over the space where there is a conglomeration of people moving in the scene. Based on ROIs, main trends of crowd motions as velocity, time-correlation and direction are modeled as templates for the observed movement distribution. Anomalies are detected when individual motion is not assigned to any of the ROIs, and the speed or direction of either crowd or individual is beyond the expected average of the ROIs template.

Zheng in (ZHENG et al., 2014) also studies crowd scene videos, but he defines a novel concept, called *gathering*, to discover group incident patterns, involving large congregations of individuals, considering areas of high density such as celebrations, parades, protests, and traffic jams. Gathering is a spatiotemporal model of activity of dense and continuing group of individuals with low mobility, wherein several members must be committed to the group during a certain time period, while others can enter and leave any time. A gathering is expected to imply something unusual or significant happening, as non-trivial group incidents in everyday life. But it does not intend to point unusual behavior of individuals or crowd.

In (ZHOU et al., 2015) a novel statistical framework is proposed to detect abnormal behaviors in crowded scene, like panic, stampedes, and accidents involving a large number of individuals. By grouping trajectories of pedestrians to form representative trajectories, which characterize the underlying motion patterns of the crowd, anomalies are detected evaluating the probability of people moves to belong or not to a specific representative trajectory. So, the anomaly is not in relation to a static area.

In short, the main goal of works on crowd video scenes is to learn the behavior pattern of the crowd and to identify anomalous behaviors of the crowd.

Another domain where unusual behavior is analyzed is in transportation systems. For instance, (LI et al., 2013b) proposed a method for reducing traffic accidents caused by pedestrian abnormal behaviors using computer vision and digital picture processing. The analysis is between position and angles of pedestrian trajectories in relation to the road structure. The proposed method detects five types of dangerous pedestrian behaviors: *road border crossing*, *illegal stopping*, *road crossing*, *walking along the border of the road*, and *entering road region*. The target object in this approach could be considered the road network, but the types of behaviors are different from those proposed in our work, and there is no ranking of pedestrian unusual behavior.

In (JIANG; WANG, 2015), dangerous vehicle behaviors are detected in surveillance video, including sharp brake, sharp turn and sharp turn brake. Jiang proposes a three step analysis: the moving object is located and tracked in the video scene; the vehicle trajectory is extracted; and the vehicle abnormal behavior is detected using the rate of velocity variation and the rate of direction change along the vehicle trajectory. Sharp turn maneuver can be considered as our return movement, but it is not in relation to a static area. Jiang uses the rate of velocity variation to detect sharp break maneuvers, but not to detect sudden acceleration movements as we do.

The work of (POPOOLA; WANG, 2012) presents a survey of different types of unusual behaviors in videos. The main difference of the works in this domain and our proposal is that in videos, unusual behavior is detected inside the area covered by the camera, and different types of data are analyzed, as the movement of objects and the background information extracted from the images. In our work we analyze the movement trajectory data outside the area covered by the camera, where no information is recorded by the video and no background information is available. In summary, we detect and measure the unusual degree of each behavior, with the main focus of ranking the moving objects according to their unusual movements.

2.2 GPS TRAJECTORY ANALYSIS

There are several works in the literature that detect unusual behaviors of moving objects, but as far as we know, there are only a few that analyze moving objects behavior in GPS trajectories and in relation to static areas. Most works in trajectory pattern mining compute behaviors of trajectories in relation to other trajectories. For instance, Laube in (LAUBE; IMFELD; WEIBEL, 2005) defines five types of movement behaviors: convergence, encounter, flock, leadership, and recurrence. Only recurrence is related to a place, similar to the surround behavior that we propose in this Master's thesis, but the recurrent visited place is extracted from the trajectory movement, while in our approach the surround is computed in relation to a given location.

In terms of unusual behavior, the work of (SIQUEIRA; BOGORNY, 2011) proposes a method to infer chasing behavior between two trajectories. Chasing pattern detection is based on time, distance, and, optionally, speed. Time is used as a minimum threshold to ensure that the objects move together during a certain period. Distance is used to guarantee that trajectories are close enough to characterize a chasing behavior. Speed is optionally used to check if both objects move with the same average velocity. Again, the analysis is made between two trajectories.

(YUAN et al., 2011) and (ZHANG; HU; YANG, 2014) focus on trajectory data mining to detect outliers. Yuan, in (YUAN et al., 2011) proposes an algorithm to detect trajectory outliers by comparing the structure of two trajectory segments. The trajectory is segmented at points where the corner angle (direction change) is bigger than the threshold. The structure similarity is computed based on comparison of direction, speed, angle, and distance. Then, the trajectory outlier is determined by its segments dissimilarities with its neighbors. (ZHANG; HU; YANG, 2014) presents a trajectory outlier detection algorithm that analyzes the location of trajectory points based speed, acceleration, and corners.

(AQUINO et al., 2013) also proposed a trajectory outilier detection method, but his focus is to add meaning to trajectory outliers considering three main reasons for a detour: stops outside the standard route, events, and traffic jams in the standard path. Outilers are identified when the amount of points of the neighbor trajectories is smaller than a neighborhood threshold, and the deviation length is higher than a minimal length. Two points are considered neighbor when their euclidean distance is less than a distance threshold.

In summary, all approaches of outlier detection analyze moving object behavior of trajectories in relation to other trajectories.

Some other works in trajectory analysis focus on identifying unusual behavior of drivers as (CHEN et al., 2013) that discovers anomalous patterns from drivers, in order to automatically detect taxi driving frauds or road network change on real-time situations. Firstly, trajectories are extracted from taxis GPS and grouped by time of occurrence, starting location and ending location. These trajectories are classified to determine the "'normal' routes between the starting and ending points at the time of occurrence. By comparing the latter route of a vehicle against time-dependent historically "normal" routes, the proposed method detects anomalous trajectories on real-time, identifies which parts of the trajectory are anomalous and gives anomalous score for trajectories based on the amount of anomalous sub-routes and the density in each sub-route. Finally, it ranks the trajectories according to their anomalous score. However, the focus of this work is not the analysis of trajectories in relation to a static target object and no other features of the trajectory are used in the analysis besides the trajectory itself.

Another anomalous trajectory detection system for unusual behavior on routes is presented in (SALEEM et al., 2013). Saleem proposes the Road segment Partitioning towards Anomalous Trajectory Detection (RPat). RPpat firstly, fetches the itinerary information of moving objects of a particular area and partitions the trajectory on the basis of road segments. Then, it evaluates these sub-trajectories independently, based on speed, traffic flow rate, time and road segment rank score, to find abnormal behavior at any intermediate parts. In this approach the segments can be considered as the target objects, since the speed, moving directions, chosen paths and time occurrence are analyzed in relation to each segment to identify anomalies. The abnormal movements are detected when the moving object: (i) overcomes the allowed speed of the segment; (ii) has unusual direction changes in the segment; (iii) choses a different route of the traffic flow of the segment; (iv) passes through the segment in restricted or unpopular time. Saleen uses the same features of trajectories that we use, but he does not define any type of abnormal behavior based on these features, as we do.

(CARBONI; BOGORNY, 2014) proposed an algorithm for finding anomalous movements and classifying driver's behavior. Trajectories are analyzed to find sub-trajectories with abrupt acceleration, abrupt deceleration and abrupt direction changes. Based on these abrupt movements, a driver is classified as: (i) *careful*, when no abrupt behavior is detected on their trajectory; (ii) *distracted*, when one abrupt movement is identified but only at places with events previously known OR at places where other trajectories present similar abrupt movement; (iii) *dangerous*, when abrupt movements are found at places without events OR more than one abrupt movement is detected where no other trajectories present similar behavior; (iv) *very dangerous*, when they have a sub-trajectory with speed above the street maximum speed limit and some of the dangerous abrupt movements were detected on their trajectories. As in our approach, speed differences are used in the analysis, and Carboni also defines different types of abrupt movements according to these differences. However, abrupt movements are extracted from individual trajectories and with the intent to classify drivers in levels of danger, while we detect abrupt movements at specific areas, around target objects.

On the other hand, Huang, in (HUANG, 2015), introduces an original approach, based on three trajectory features: turns and their density; detour factor; and route repetition, to find where the driver's behavior shows anomalies such as taking a wrong turn, performing a detour, or losing the way because of orientation problems. The main difference of this work and our proposal is clear since the types of behavior are different and the trajectory analysis is not in relation to static areas.

The work of (SHEN; LIU; SHANN, 2015) first describes the scenario of roaming behaviors related to planned crimes, and then derives formal specifications for detecting suspicious roaming events from vehicle trajectories according to specialist consultants, like police investigators. Based on scenario and assumptions of roaming events to commit a premeditated crime, potential suspicious vehicles are identified and their intentions are evaluated according to circling activities, relative driving speed and time dispersion. Lastly, a weighting scheme is provided to rank all of the abnormal events. Roaming behavior has a similar concept as our surround, but again, it is not in relation to static areas.

Abnormal behavior detection in maritime traffic is also a need in routine surveillance operations. For instance, (SHAHIR et al., 2014) proposes a multi-vessel interaction and anomaly detection framework to identify and differentiate a range of interaction patterns. The anomalies of interest are marine vessels that operate over some period of time in relative proximity to each other or some offshore structure. The analysis of this work is a generalization of the concept of *rendezvous*, which generally occurs only when the related entities are "close enough" and engaging in some type of "distinctive interaction". Shahir's framework detects six anomalous situations: *collision*, *refuelling*, *towing*, *rescuing*, *piracy* and *smuggling* the based on contextual, geospatial, kinematic factors like vessel type, speed, heading, geographic location, time window, the number and type of vessels, and geometric aspects such as the relative size of the rendezvous point or cyclic movement pattern. In this paper the vessel or the offshore structure can be considered as the target object, and the shore can be considered as the ROI, but the anomalies detected are neither assigned to the trajectory nor to moving objects and the types of anomalous behaviors are different from our proposal.

(LETTICH et al., 2016) proposes a framework which defines the avoidance between pairs of trajectories considering changes of behavior and a criteria to classify any avoidance as weak, mutual or individual. The avoidance concept is defined according to two predicates. The fact that two trajectories become sufficiently close to be considered in contact, and, the forecast of these trajectories on a maximum time threshold to look ahead will lead to a contact. Weak, individual or mutual avoidance are classified respectively when, one or both trajectories present minor changes in their movements, only one trajectory presents a relevant change, or both trajectories alter significantly, changing their movement in order to cause a missed meet.

To the best of our knowledge, the only work very close to our approach, and that can be compared, is the avoidance behavior proposed in (ALVARES et al., 2011). This is because the focus of his method is to find suspicious behaviors of trajectories of moving object that, explicitly, avoid going towards a predefined fixed object. In other words, he also looks for unusual behavior of individuals in relation to predefined fixed areas, as we do. However he only detects one behavior, the *avoidance*.

Figure 2 and 3 show some trajectory behaviors in relation to static objects o_1, o_2 and o_3. In (ALVARES et al., 2011), the specific static object or area to be avoided is called as *target object*. The region that involves the target object is called ROI (Region Of Interest), where the moving objects are able to notice the target object and either have a change of behavior or not. According to (ALVARES et al., 2011), τ_1 in Figure 2(a) has a standard behavior as the moving object crosses the target object o_1 keeping its original direction. τ_2 in Figure 2(b), despite of changing its direction inside the ROI and passing by the region of interest more than once, it crosses the target object. Therefore it is also considered standard behavior in the work of (ALVARES et al., 2011).

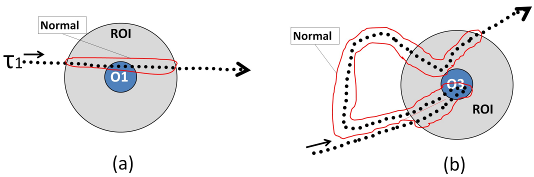

Figure 2 – Trajectories classified as standard behavior inside ROI.

On the other hand, τ_3 and τ_4 in Figure 3(a) have avoidance behavior, because they change their original direction inside the ROI in order to avoid the target object.

The behavior of trajectory τ_2 (Figure 3(b)) when it enters the ROI of target object o_3 for the second time is not detected by the method proposed by (ALVARES et al., 2011) because τ_2 crossed o_2 at the first time it passed through the ROI. The behaviors of τ_5, τ_6 and τ_7 (Figure 3(c)) around target object o_2 are also not identified in his approach, either because their strangeness are mostly related to duration, speed or sharp turns or because they do not have a minimum distance moving towards the target object, since such characteristic is mandatory to detect *avoidance* behavior.

In this Master's we define the concept of *unusual behavior* to identify different types of behaviors in relation to a target object. An *unusual behavior* is detected when the moving object has any behavior difference, in terms of duration (τ_5 Figure 3(c)), speed (τ_6 Figure 3(c)) or direction (τ_7 Figure 3(c)), from the expected standard behaviors in relation to a target object and inside the ROI.

We introduce three new unusual behaviors: *surround*; *escape*;

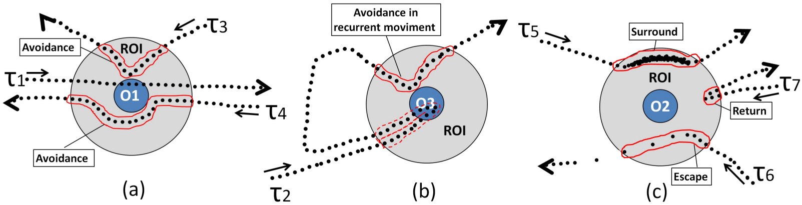

Figure 3 – Trajectory with unusual behaviors.

and *return*. Based on these three new behaviors and the avoidance proposed by (ALVARES et al., 2011), we present a new algorithm to both compute these behaviors and rank the moving objects in relation to a set of target objects, considering different unusual behavior recurrence cases.

Table 1 sumarizes the main differences between our approach and the related works found in the literature that have some similarities with our proposal.

Table 1 – Comparative between related works and MOUB.

Author	Type of data	Behavior in relation to	Behaviors detected	Ranking
Aquino et al. (2013)	GPS	trajectories	stop outlier, event outlier, traffic avoiding outlier	
Alvares et al. (2011)	GPS	pre-defined fixed target object	avoidance	X
Burghouts, G. et al (2014)	camera	truck	fight, fiddle/check, loiter, run	
Carboni, Bogorny (2014)	GPS	none	careful, distracted, dangerous, very dangerous	
Chen et al. (2013)	GPS	time of occurrence and start / end location	anomalous	X
Huang (2015)	GPS	road	wrong turn, detour, losing way	X
Lettich et al. (2016)	GPS	weak, mutual or individual avoidance	wrong turn, detour, losing way	X
Li, X. et al. (2013)	camera	road	road border crossing, illegal, stopping, road crossing and walking/ entering road region	
Merki (2012)	GPS	trajectories	pursuit and escape, avoidance, and confrontation	
Saleem et al. (2013)	GPS	road segments	abnormal	X
Siqueira, Bogorny (2011)	GPS	trajectory	chasing	
Yuan et al. (2011)	GPS	trajectories segments	outlier	
Zhang; Hu; Yang, (2014)	GPS	trajectories	outlier	
Ranking MOUB	GPS	pre-defined fixed target object	surround, escape, return, avoidance	X

3 FUNDAMENTALS

To the correct understanding of the proposed approach, we firstly introduce the concepts of trajectory and target object.

Definition 1. *Trajectory.* A trajectory is an ordered list of space-time points $\langle p_0, p_1, \dots, p_n \rangle$, where $p_i = (x_i, y_i, t_i)$ and $x_i, y_i \in \mathbb{R}$, $t_i \in \mathbb{R}^+$ for $i = 0, \dots, n$ and $t_0 < t_1 < \cdots < t_n$.

It is well known that several trajectory patterns do not hold for an entire trajectory, but only in a trajectory part, which is called sub-trajectory. The concept of sub-trajectory is formally given in Definition 2.

Definition 2. *Sub-trajectory.* Let $\tau = \langle p_0, p_1, ..., p_n \rangle$ be a trajectory. A sub-trajectory s of τ is a list of consecutive points of τ $\langle p_i, p_{i+1}, p_{i+2}, ..., p_m \rangle$, where $\forall j:\ i \leq j \leq m,\ p_j \in \tau$.

We analyze the behavior of moving objects in relation to static objects/areas. These static objects are called *target objects*, introduced in (ALVARES et al., 2011). *Target objects* are all places that are the target of study, i.e., any place that is used as target to identify the behavior of a moving object around it. Target objects can be, for instance, the monitoring cameras in a town, important buildings that can be target of terrorist attack, etc.

Definition 3. *Target object.* A target object is an object o with a convex geometry and an area greater than zero. An object represented by a point or line should be involved by a radius of given size r_o, in order to have an area greater than zero, representing the coverage area of the target object where individuals might go through.

Figure 4(a) shows an example of circular object in black and its target object, the blue area create based on the given radius r_o.

In order to analyze the behavior of moving objects around a target object, we introduce the concept of region of interest (ROI). The region of interest is the area around a target where moving objects may either change or not their behavior, because of the target. Objects moving far from the target, outside the region of interest, are not influenced by the target, therefore, they do not need to be analyzed. Inside the region around the target, the moving object is able to notice the target object, and change or not its behavior.

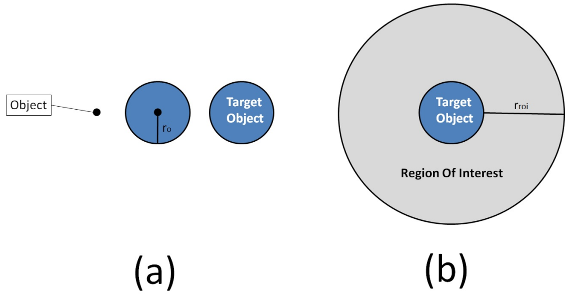

Figure 4 – Target Object and Region of Interest example.

Definition 4. *Region Of Interest (ROI).* The region of interest ROI of the target object o is the area of the target object o increased by a radius of given size r_{roi}.

Figure 4(b) shows an example of region of interest (ROI), which is the gray are around the target object, created based on the given radius r_{roi}.

In our work, we only analyze parts of trajectories that intersect the ROI, so we introduce the concept of *sub-trajectory into ROI*. We call *sub-trajectory into ROI* all trajectory points that intersect the ROI of a specific target object, as given in Definition 5.

Definition 5. *Sub-trajectory into ROI.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory and $s = \langle p_j, p_{j+1}, p_{j+2}, ..., p_k \rangle$ be a sub-trajectory of τ. s is a *sub-trajectory into ROI* of τ if and only if, $(s \cap ROI) = s \wedge (p_{j-1} \cap ROI) = \emptyset \wedge p_{k+1} \cap ROI = \emptyset$.

Figure 5 shows two examples of sub-trajectories into ROI. s_1 of τ_1 starts at p_{12} and finishes at p_{33}, and s_1 of τ_2 starts at p_{17} and finishes at p_{34}.

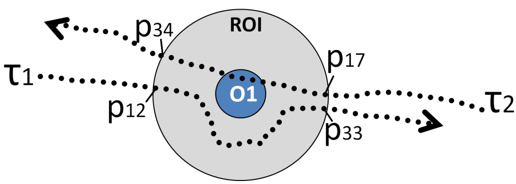

Figure 5 – Sub-trajectories into *ROI*

Inside a ROI, there might exist a sub-trajectory, which goes towards the target object. Along this Master's thesis, we refer to this sub-trajectory as *sub-trajectory directed to the target*. Sub-trajectory direct to the target is the longest part of the sub-trajectory into ROI that moves towards the target object.

Differently from (ALVARES et al., 2011) that demands a minimum distance traveled by the moving object towards the target object inside a ROI to characterize a *sub-trajectory directed to the target*, we define that a sub-trajectory directed to the target must have at least three points moving towards the target. With three points it is possible to avoid noise (points wrongly collected) and detect the movement direction in relation to the target, even for short movements. Definition 6 gives the formal definition of sub-trajectory directed to the target.

It is worth mentioning that we keep the *minimum length* threshold to identify avoidance behaviors, as proposed in (ALVARES et al., 2011), but for the new behaviors we propose in this work we analyze all movements inside the ROI.

Definition 6. *Sub-trajectory directed to the target.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory, s be a sub-trajectory into ROI of τ and $sin = \langle p_j, p_{j+1}, p_{j+2}, ..., p_k \rangle$ be a sub-trajectory of s. sin is a *sub-trajectory directed to the target* of s, if and only if, $(dist(p_j, p_k) \geq dist(p_j, p_x)) \wedge (line(p_j, p_k) \cap o \neq \oslash) \wedge (line(p_j, p_x) \cap o \neq \oslash) \wedge size(sin) \geq 3$, where $j < x < k$, $dist$ is a function that returns the euclidean distance between two points, $line$ is a function that returns a line extended in forward direction, and $size$ is a function that returns the number of points of sin.

Figure 6 presents an example of the calculation of sub-trajectory directed to the target sin_1 of τ_1. Considering the first trajectory point inside the ROI (p_5 in Figure 6) as initial point and taking the next points, one by one, the projected line segment from the considered initial point to the considered last point (p_6 in Figure 6) is extended to check if the trajectory is going towards the target object. The transition between Figure 6(a) - (b) shows that if the extended line segment (Figure 6(a)) does not cross the target object, then the initial point of sub-trajectory into ROI becomes the previous considered last point(new initial point) and the considered last point becomes the next point of the sub-trajectory into ROI (p_7 in Figure 6(b)).

If the new extended line segment crosses the target object, the procedure is repeated only with the next points (Figure 6(c)(d)) until the line segment does not cross the target object (Figure 6(e)). Then, the points between the initial and last point, in which the line segment is the biggest and intersects the target object, composes the sub-trajectory directed to the target sin_1 (Figure 6(f)).

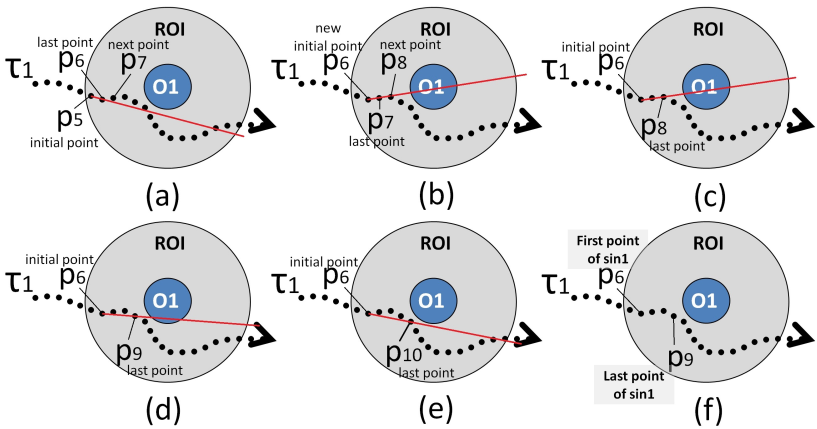

Figure 6 – Extended line segment over the ROI: (a) from p_5 to p_6; (b) from p_6 to p_7; (c) from p_6 to p_8. (d) from p_6 to p_9; (e) from p_6 to p_{10}. (f) Sub-trajectory directed to the target from p_6 to p_9 calculated for τ_1.

Figure 6 (f) presents the sub-trajectory directed to the target of τ_1, that comprehends points from p_6 to p_9. After having a sub-trajectory directed to the target, the moving object changes its direction, avoiding to intersect the target object. This characterizes an *avoidance* behavior (ALVARES et al., 2011).

Definition 7. *Avoidance.* Let o be a target object. Let s be a sub-trajectory into ROI and sin be a sub-trajectory directed to the target of s. s has an *Avoidance* pattern in relation to a target object o, if and only if, $\exists\ sin \in s \mid length(sin) > minLength \wedge (s \cap o) = \emptyset$, where $length$ is a function that returns the sub-trajectory length and $minLength$ is the minimum length of the sub-trajectory directed to the target.

Based on the previous concepts, in the following chapter we propose new types of unusual behavior patterns.

4 PROPOSED UNUSUAL BEHAVIORS

An unusual behavior is any type of movement behavior, that in terms of duration, speed or sharp turns in relation to a target object inside a ROI, is different from the standard behavior of trajectories inside the same ROI. Therefore, we firstly define the standard behaviors inside a ROI, once the unusual movements will be compared to normal ones. The *standard behavior* is characterized by moving objects that cross the target object. More formally, Definition 8 gives the concept of *standard sub-trajectory into ROI*.

Definition 8. *Standard Sub-trajectory into ROI.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory and s be a sub-trajectory into ROI of τ. s is a *Standard Sub-trajectory into ROI* of τ if and only if $s \cap o \neq \oslash$.

In the following sections we present three new unusual behaviors: *surround*, *escape*, and *return*. It is worth mentioning that the avoidance pattern is also considered in our work as a type of unusual behavior, and that a single sub-trajectory into ROI may present more than one unusual behavior.

4.1 SURROUND

A surround behavior is observed when the moving object enters the ROI, stays during a long time without intersecting the target object, and leaves the ROI, without intersecting the target. Figure 7 shows some examples of trajectories with *Surround* pattern. Trajectory τ_1 enters the ROI, stays for a while and leaves the ROI going back. Trajectory τ_2 enters the ROI, stays during a long time moving on the same path, very close to the target object, and then, leaves the ROI. Trajectory τ_3 enters the ROI, moves around the target object three or four times and leaves the ROI. Trajectory τ_4 enters the ROI, moves for a while at a certain distance from the target object, and leaves the ROI.

On the other hand, Figure 8 shows some trajectories that do not present a *Surround* behavior. Trajectory τ_5 enters the ROI, moves around the target object for some time, but intersects the target object when leaving the ROI. Trajectory τ_6 moves close to the target object during a very short time, then leaves the ROI. Trajectory τ_7 stays

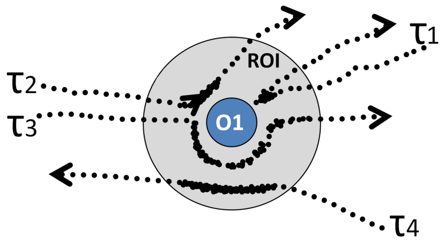

Figure 7 – Trajectories with surround behavior.

during a long time moving nearby, but outside the ROI, so τ_7 will not be the focus of studying.

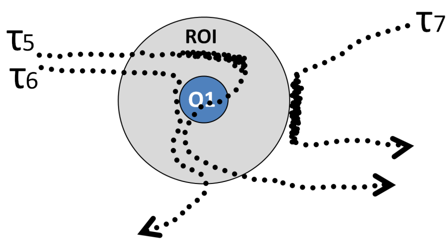

Figure 8 – Trajectories without surround behavior.

The time spent into ROI by trajectories τ_1, τ_2, τ_3 and τ_4 can just be measured when looking at the time information, even though it is possible to have an idea about how long the moving object stays around the target object by the amount of tracking points inside a ROI. However, this is not enough to detect a surround behavior.

To compute a *Surround*, we compare the *duration* of the sub-trajectories into ROI which do not cross the target object with the duration of all *standard sub-trajectories into ROI* at the same target object. Based on the standard sub-trajectories into ROI, we introduce the *surround duration threshold.* We call *surround duration threshold* the minimal time that a sub-trajectory should spend into ROI to characterize a surround behavior. It is calculated according to the *average duration* and *standard deviation* of standard sub-trajectories into ROI, and makes use of a sensitivity parameter of surround.

Definition 9. *Surround duration threshold.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory and ss, be a *standard sub-trajectory into ROI* of τ, as specified in Definition 8. Let γ_S be the sensitivity parameter of surround. The *surround duration threshold minD* of the target object o is defined as

$$minD = \mu + \sigma \times \gamma_S \tag{4.1}$$

The average duration μ and standard deviation σ are given by Equations 4.2 and 4.3, respectively

$$\mu = \frac{\sum_{i=1}^{n}(Duration(ss_i)}{n} \tag{4.2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}[Duration(ss_i) - \mu]^2}{n}} \tag{4.3}$$

where $Duration(x)$ is a function that returns the duration of a sub-trajectory x and n is the number of standard sub-trajectories into ROI at the target object o. This threshold helps avoiding to define a surround behavior when individuals stay at a bank, school, supermarket, or any area for a long time, either working or waiting. In such areas, the standard behavior will be a long time stay, but intersecting the target object.

A trajectory presents a *surround* behavior in relation to a target object when its sub-trajectory into ROI does not intersect the target object at any time during its movement inside the ROI, and the duration of its sub-trajectory into ROI is greater than the surround duration threshold (Definition 9) of the same target object.

Definition 10. *Surround.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory and s be a sub-trajectory into ROI of τ. s has a *surround* pattern S at the target object o if and only if $s \cap o = \oslash \wedge Duration(s) > minD$, where $minD$ is the surround duration threshold at o.

Even if we can identify trajectories as those in Figure 7 that have a surround pattern, we are not able to say accurately which of them present the strongest characteristics of surround behavior at the target object. To know how unusual the surround behavior of a trajectory is in relation to a target object, we go one step further and give a degree of unusual behavior, called *local score*. *Local score* is a function that, given an unusual behavior of a trajectory τ at the target object o, it returns a value, between 0.5 and 1, indicating how unusual this behavior is in relation to trajectories with standard behavior at the same target object o. The local score for surround is defined by

$$L_s(S) = 1 - \frac{minD}{Duration(s)} \times \frac{1}{2} \tag{4.4}$$

where s is the sub-trajectory into ROI with surround, according to Definition 10. We define the score between 0.5 and 1 to be in the same range of the avoidance.

4.2 ESCAPE

A escape pattern is mainly characterized by a sub-trajectory with an increase of speed inside the ROI, apparently to escape from the target object. The moving object enters the ROI, and after having a sub-trajectory directed to the target, it leaves the ROI much faster than it entered the ROI, without intersecting the target object.

Figure 9 shows some examples of trajectories with *Escape* behavior, where the change of speed inside the ROI is clearly noticed by the difference of the distance between the points of the sub-trajectories. Trajectory τ_1 in Figure 9(left) moves in direction to the target object o_1 (point p_{10} to p_{13}) and suddenly, the speed of τ_1 increases leaving the ROI (p_{14} to p_{16}) with a much higher speed than it entered the ROI. Trajectories τ_2 and τ_3 Figure 9(right) avoid the target object o_2 and have sub-trajectories directed to the target with the minimum length, so in the approach of (ALVARES et al., 2011) they are identified as avoidance behaviors. However, as both have a speed increasing inside the ROI, we also identify a escape behavior. τ_2 has the highest speed from point p_{18} to p_{22}, and τ_3 has the highest speed from p_{17} to p_{20}.

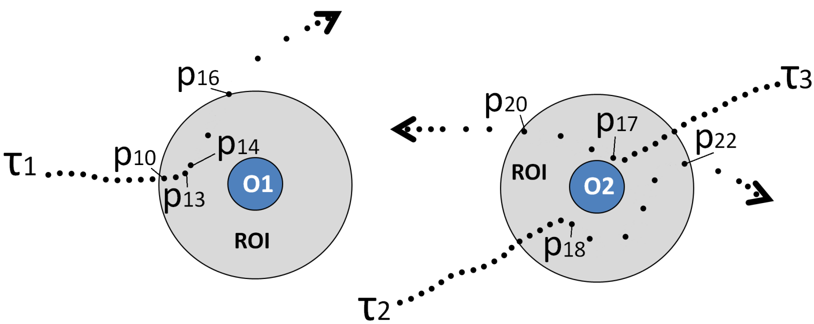

Figure 9 – Trajectories with escape behavior.

Figure 10 presents some examples of trajectories which do not characterize a *escape* behavior. Trajectory τ_4 has a sub-trajectory directed to the target and its speed leaving the ROI is much higher than the speed of entrance, but it crosses the target object o_3. τ_5 increases its speed, but does not enter the ROI, so it is not aware of the target object o_3.

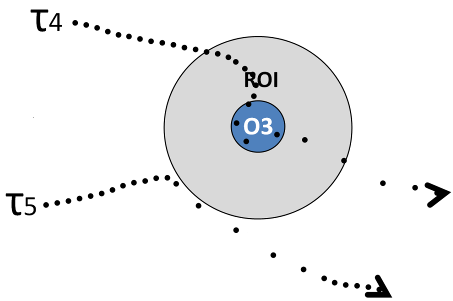

Figure 10 – Trajectories without escape behavior.

The first step to identify a *escape* behavior is to distinguish the part of the trajectory that is moving towards the target object (sub-trajectory directed to the target) from the part leaving the ROI. Therefore, we introduce the concept of *sub-trajectory of way out*. Given a sub-trajectory into ROI and a sub-trajectory directed to the target, a sub-trajectory of way out is the one starting after the last point of sub-trajectory directed to the target and finishing at the last point of sub-trajectory into ROI. More formally:

Definition 11. *Sub-trajectory of way out.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory, $s = \langle p_j, p_{j+1}, p_{j+2}, ..., p_k \rangle$ be a sub-trajectory into ROI of τ. Let $sin = \langle p_q, p_{q+1}, p_{q+2}, ..., p_w \rangle$ be the sub-trajectory directed to the target of s. A sub-trajectory of way out $sout = \langle p_{w+1}, p_{w+2}, ..., p_k \rangle$ of s is the sub-trajectory into ROI s beginning at the point p_{w+1} and ending at the last point of s, i.e. p_k.

Notice that a trajectory that does not have a sub-trajectory directed to the target will not have a sub-trajectory of way out.

Figure 11 shows how to identify the sub-trajectory of way out. Figure 11(a) presents the sub-trajectory into ROI s_1, that goes from $p_j = p_8$ to $p_k = p_{23}$. Figure 11(b) shows a sub-trajectory directed to the target, whose first point is $p_q = p_8$ and last point is $p_w = p_{12}$.

Figure 11(c) shows the sub-trajectory of way out, that is the set p = $\langle p_{13}, p_{14}, ..., p_{23}\rangle$ of s, since $p_{12} < p_u \leq p_{23}$.

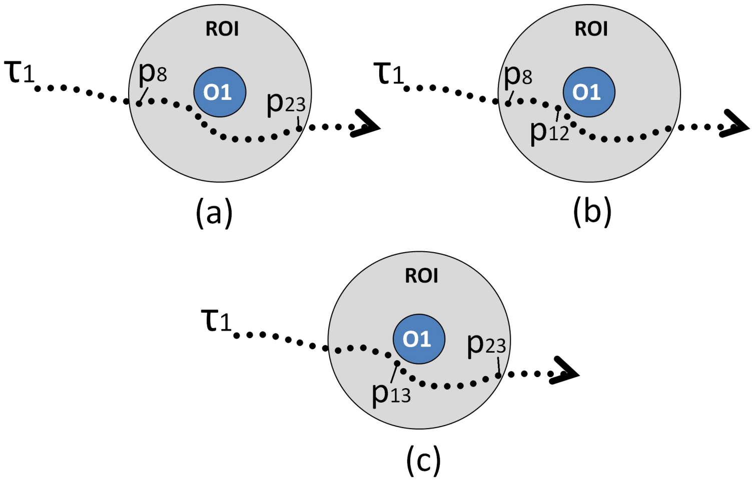

Figure 11 – (a) Sub-trajectory into ROI (b) Sub-trajectory directed to the target (c) Sub-trajectory of way out

To establish how much a trajectory must increase its speed to characterize a escape behavior, we introduce the concept of *escape speed threshold*. We call *escape speed threshold* the lowest increase of speed that a trajectory needs to have into a ROI to characterize a escape behavior. It is calculated according to the *average speed* and *standard deviation* of the difference of speed between the sub-trajectory of way out and the sub-trajectory directed to the target of standard sub-trajectories into ROI, and makes use of a sensitivity parameter of speed, similarly to the surround. We use the speed of entrance of every sub-trajectory to evaluate the speed behavior against the standard speed behavior of the region because if the majority of the trajectories have a low speed, this is the standard speed behavior at the target object.

Definition 12. *Escape speed threshold.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory and ss be a standard sub-trajectory into ROI of τ. Let γ_E be the sensitivity parameter of escape. The *escape speed threshold* $minV$ of target object o is defined by

$$minV = \mu + \sigma \times \gamma_E \tag{4.5}$$

The average speed μ and standard deviation σ of standard sub-trajectories are given by Equations 4.6 and 4.7, respectively

$$\mu = \frac{\sum_{i=1}^{n}[Speed(sout_i) - Speed(sin_i)]}{n} \tag{4.6}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\{[Speed(sout_i) - Speed(sin_i)] - \mu\}^2}{n}} \tag{4.7}$$

where Speed(x) is a function that returns the average speed of a sub-trajectory x, n is the number of ss_i at the target object o, sin_i is the sub-trajectory directed to the target of ss_i and $sout_i$ is the sub-trajectory of way out of ss_i.

A trajectory has a *Escape* behavior in relation to a target object when the sub-trajectory into ROI does not intersect the target object and the difference between the speed of sub-trajectory of way out and sub-trajectory directed to the target is higher than the escape speed threshold at the same target object. More formally:

Definition 13. *Escape.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory. Let s be a sub-trajectory into ROI of τ. Let sin be the sub-trajectory directed to the target of s. Let $sout$ be the sub-trajectory of way out of s. s has a *escape* pattern E, if and only if, $(Speed(sout) - Speed(sin)) > minV$, where $minV$ is the escape speed threshold at o.

Looking at the escape behavior of trajectories in Figure 9, we can notice that the escape characteristics of trajectory τ_1 are stronger than the escape characteristics of trajectories τ_2 and τ_3. Trajectory τ_1 is faster than trajectories τ_2 and τ_3, because the distance between every two points of τ_1 is higher than the distance between every two points of τ_2 and τ_3.

To know, accurately, how unusual the escape behavior of a sub-trajectory into ROI s is at the target object o, we define the *local score for escape*:

$$L_s(E) = 1 - \frac{minV}{Speed(sout) - Speed(sin)} \times \frac{1}{2} \tag{4.8}$$

where $minV$ is the escape speed threshold at o, $sout$ is the sub-trajectory of way out of s, and sin is the sub-trajectory directed to the target of s. With this formula, L(E) varies between 0.5 and 1.

4.3 RETURN

A return behavior is characterized by a moving object entering the ROI, going towards the target object, returning, and leaving the ROI before intersecting the target object.

Figure 12 shows two trajectories with *return* behavior: trajectory τ_1 enters the ROI, has a sub-trajectory directed to the target and returns through the same path; trajectory τ_2 enters the ROI, has a sub-trajectory directed to the target and returns very close to its sub-trajectory directed to the target.

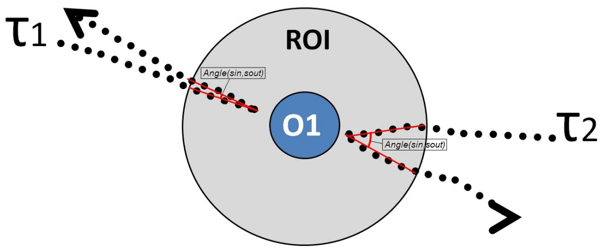

Figure 12 – Trajectories with *return* behavior.

To identify a *return* behavior we have to check if a moving object is going back in relation to the target object.

Definition 14. *Return.* Let o be a target object and ROI be the region of interest of o. Let τ be a trajectory. Let s be a sub-trajectory into ROI of τ, sin be the sub-trajectory directed to the target of s and $sout$ be the sub-trajectory of way out of s. s has a *Return* pattern in relation to o, if and only if, $(s \cap o = \emptyset) \wedge Angle(sin, sout) < maxAngle$, where $maxAngle$ is the maximum angle between sin and $sout$ to characterize a return behavior, and Angle(x,y) is a function that returns the angle between the line defined by the first point and last point of the sub-trajectory x and the line defined by the first point and last point of sub-trajectory y.

Notice that the return behavior of trajectory τ_1 (Figure 12) is stronger than the return of trajectory τ_2 (Figure 12), because τ_1 returns close to the same way of entrance, with a clear intent of returning in relation to its original movement. For trajectory τ_2 this is not so obvious, because its back movement is a little far from its entrance path.

We measure the return behavior in relation to a target object with a *local score*, given by Equation 4.9, that calculates how unusual the return behavior of a sub-trajectory s is at the target object o.

$$L_s(R) = 1 - \frac{Angle(sin, sout)}{maxAngle} \times \frac{1}{2} \tag{4.9}$$

where sin is the sub-trajectory directed to the target of s, $sout$ is the sub-trajectory of way out of s and $maxAngle$ is the maximum angle to characterize a return behavior. L(R) is defined in the interval [0.5 , 1].

5 RANKING MOVING OBJECTS WITH UNUSUAL BEHAVIORS - THE RANKING MOUB ALGORITHM

Considering the previous definitions of different types of unusual behavior and their local scores, we only identify unusual behavior of trajectories in relation to a single target object. But, what happens if a moving object goes through a region with several target objects? For instance, a person moving in the city center, where there are many regions to commit a crime, such as banks, atm, bus stop, restaurants, gas station, there is a high probability that the moving object intersects more than one ROI and in each ROI it may present distinct unusual behaviors. To measure the behavior of objects in relation to all ROIs, in Section 5.1 we introduce a *global score* to measure how unusual the behavior of a moving object is in its history. In Section 5.2 we present the ranking MOUB (Moving Object Unusual Behavior) Algorithm.

5.1 MEASURING THE GLOBAL UNUSUAL BEHAVIOR

The *global score* is the unusual behavior degree of a moving object along its whole movement, considering every ROI it goes through. We compute the *global score* using: (i) the local score of every unusual behavior type; (ii) the *unusual behavior weight* per target object, that is a measurement of how frequent unusual behaviors are at the target object; and (iii) *the moving object percentage of unusual behavior*, which is a degree of comparison to all other moving objects with the same unusual behavior at the same target object.

It is important to dynamically compute the weight of each target object because it avoids to identify false unusual behaviors. Inside a ROI where most trajectories do not intersect the target object, the unusual behaviors should not be detected or should be less unusual than an unusual behavior detected inside a ROI where most of the trajectories have standard sub-trajectories. The weight w_o is given by

$$w_o = 1 - \frac{\sum_{j=1}^{m} f(L_j)}{m} \tag{5.1}$$

where o is the target object and ROI_o its region of interest, m is the total number of sub-trajectories into ROI_o, j is each of the m sub-trajectories into ROI_o, L_j is the local score of j and $f(L_j)$ is a function that returns 1 if j has unusual behavior in relation to the target object

o, i.e. $L_j \neq 0$, and 0 otherwise.

The unusual behavior percentage per target object is very significant, as trajectories with a recurrent unusual behavior must have a higher *global score* than trajectories with less unusual behaviors of the same type at the same target object. The percentage $p_{\tau s_i o}$ is given by

$$p_{\tau s_i o} = \frac{\sum_{c=1}^{u} f(s_c)}{u} \tag{5.2}$$

where u is the number of sub-trajectories into ROI_o with the same unusual behavior of s_i, c is each of the u sub-trajectories into ROI_o and $f(s_c)$ is a function that returns 1 if the sub-trajectory into ROI_o s_c is a sub-trajectory of τ, else returns 0.

Having defined the relative unusual behavior percentage, we now define the *global score*.

Definition 15. *Global score.* Let τ be a trajectory, n be the total number of sub-trajectories into ROI of τ that do not have any unusual behavior, let k be the number of unusual behaviors of τ. The *global score* $G_{\tau O}$ of τ in relation to the set O of target objects is defined by

$$G_{\tau O} = \frac{\sum_{i=1}^{k} L_i \times w_o \times p_{\tau i o}}{n + k} \tag{5.3}$$

where i is each of the k unusual behaviors of τ, L_i is the local score of i, w_o is the weight of the target object o and $p_{\tau i o}$ is the unusual behavior percentage of i at the target object o.

5.2 THE RANKING MOUB ALGORITHM

According to the definitions and equations in previous chapters, we present, in Listing 5.1, an algorithm to compute the unusual behaviors and rank the moving objects according to their unusual movements.

Listing 5.1 – Pseudo-code of the proposed Ranking MOUB algorithm

```
Input:  T //set of trajectories
        O //set of target objects
        r //size of the buffer for the region of interest
Output: UB //set of sub-trajectories with unusual behavior
  MOUB //ordered list of moving objects with unusual behavior
Method:
SS = [], UB = [], minD = 0, minV = 0
for each τ_i ∈ T | intersects(τ_i, buffer(O,r)) do
  for each o_k ∈ O do
    τ_i.s = getSubtrajectoriesIntoROI(τ_i, o_k, r)   //Def. 5
    for each s_j ∈ τ_i.s do
      s_j.o_k = o_k
      s_j.sin = getSubtrajectoryDirectedToTheTarget(s_j, o_k)   //Def. 6
      s_j.sout = getSubtrajectoryOfWayOut(s_j, o_k)   //Def. 12
      if intersects(s_j, o_k)
        SS.add(s_j)
      else
        UB.add(s_j)
    endfor
  endfor
endfor
minD = SurroundDurationThreshold(SS, γ_S, O)   //Equation 4.1
minV = EscapeSpeedThreshold(SS, γ_E, O)   //Equation 4.5
for each s_j ∈ UB do
  auxS = s_j
  if Duration(s_j) > minD_k
    auxS.pattern = "Surround"
    auxS.L = 1 − (minD_k / Duration(s_j)) × 1/2   //Equation 4.4
    UB.add(auxS)
  if Speed(s_j.sout) − Speed(s_j.sin) > minV_k
    auxS.pattern = "Escape"
    auxS.L = 1 − (minV_k / (Speed(s_j.sout)−Speed(s_j.sin))) × 1/2   //Equation 4.8
    UB.add(auxS)
  endif
  if Angle(s_j.sin, s_j.sout) < maxAngle
    auxS.pattern = "Return"
    auxS.L = 1 − (Angle(s_j.sin,s_j.sout) / Θ) × 1/2   //Equation 4.9
    UB.add(auxS)
  endif
  if s_j.sin > minLength
    auxS.pattern = "Avoidance"
    if intersects(s_j, CR(s_j))
      auxS.L = 1
    else
      auxS.L = 0.5
    endif
    UB.add(auxS)
  endif
  if(auxS.L == 0)
    SS.add(auxS)
  endif
  UB.remove(s_j)
endfor
for each τ_i ∈ T | intersects(τ_i, buffer(O,r)) do
    for each s_j ∈ UB | s_j ⊂ τ_i do
      τ_i.G_O = τ_i.G_O + s_j.L×weight(s_j.o_k)×percentage(τ_i, s_j, s_j.o_k) //Equation 5.3
    endfor
  τ_i.G_O = τ_i.G_O / (SS.size+UB.size)
  MOUB.add(τ_i)
endfor
MOUB.sortBy(G_O)
return UB, MOUB
```

The main input is: a set of trajectories T; a set of target objects O; and a radius for the region of interest. Other input parameters are: a minimum length for sub-trajectory directed to the target; a sensitivity value of surround; a sensitivity value of escape; and a maximum angle to characterize the return behavior. We give default values for these parameters, but they can be modified according to a specific application. These default values are $minLength = 30\%$ of the ROI size as the minimal length for the sub-trajectory directed to the target, $\gamma_S = 3$ for the sensitivity parameter of surround, $\gamma_E = 3$ for the sensitivity parameter of escape, and $\Theta = 45°$ for the maximum angle to characterize a return behavior.

The algorithm output (line 62) is the set of unusual behaviors (UB) detected for every moving object at each target and the moving object ranking ($MOUB$).

The algorithm is divided in three main loops. In the first one (lines 8-21), for each sub-trajectory into ROI, the sub-trajectory directed to the target and the sub-trajectory of way out are computed. If the sub-trajectory into ROI intersects the target object (line 15) it is a standard sub-trajectory and it is stored into SS (line 16). Otherwise, it is added to the UB structure (line 18).

The thresholds $minD$ and $minV$, used to calculate surround and escape, respectively, are computed in lines 22-23. The SurroundDurationThreshold function (line 22) returns the surround threshold computed for each target object, as specified in Definition 9. The EscapeSpeedThreshold function (line 23) returns the escape speed threshold computed for each target object, as specified in Definition 12. These functions have as input parameters O, that is the set of target objects, SS, that is the set of standard sub-trajectories into ROI, γ_S that is the sensitivity value of surround and γ_E, that is the sensitivity value of escape.

The second loop (lines 24-53) identifies the unusual behaviors according to their definitions in Chapters 3 and 4. A sub-trajectory might have more than one unusual behavior, which are: *surround* if the sub-trajectory duration is longer than the surround duration threshold (line 26); *escape* in case the sub-trajectory increasing of speed inside the ROI is higher than the escape speed threshold (line 30); return whenever the sub-trajectory moves back (line 62); and avoidance if the sub-trajectory has a minimum length directed to the target and avoids the target object.

For every case, the type of behavior and local score are assigned to the sub-trajectory. The local scores of surround (line 28), escape (line 32) and return (line 37) are calculated as specified in Equations 4.4, 4.8 and 4.9, respectively. On the other hand, the local score of avoidance is computed considering the confidence incremental region (see (ALVARES et al., 2011) for more details), where if the sub-trajectory crosses the confidence incremental region (line 42) the *local score* $= 1$, and 0.5 otherwise.

Finally, in the third loop (lines 54-60), the moving objects are ranked according to Equation 5.3. For every trajectory $\tau_i \in T$ that intersects some ROI (line 54), the global score of τ_i is, repeatedly increased by $s_j.L \times \text{weight}(s_j.o_k) \times \text{percentage}(\tau_i, s_j, s_j.o_k)$, where $s_j.L$ is the local score of the sub-trajectory s_j of τ_i at o_k, according to Definitions 4.4, 4.8 and 4.9, $\text{weight}(s_j.o_k)$ and $\text{percentage}(\tau_i, s_j, s_j.o_k)$ returns, respectively, w_o and $p_{\tau io}$ of Equation 5.3, which are the weight of o_k, and the percentage of sub-trajectories that have the same unusual behavior of s_j at o_k. This loop is repeated while exists a sub-trajectory s_j of τ_i into ROI_k with unusual behavior.

Indeed, the moving objects global score, depends on the degree of unusual behavior computed in every single ROI, the frequency of unusual behaviors in every single ROI considering all sub-trajectories that cross it, and the number of the same kind of unusual behavior presented by other moving objects at every single ROI. The complexity of the algorithm is $O(n^2)$ where O is the number of targets and n is the total of trajectory points

In Section 5.3, we demonstrate, step by step, how to compute the moving object global score, calculating the target object weight and the percentage of unusual behavior per sub-trajectory per target object.

5.3 PROOF OF CONCEPT

In order to better understand how to compute the moving object global score, we run a case study with two target objects and nine moving objects, in which, we are going to compute the global score of moving object M_6. Figure 13 shows target objects o_1 and o_2, and the trajectory of each of the nine moving objects.

The first step to compute the moving object global score is to identify the unusual behavior type and local score of every sub-trajectory into ROI.

Trajectory τ_6 (Figure 13) has two sub-trajectories into ROI_{o_2}, s_1 and s_2. Both sub-trajectories have a surround behavior in relation to o_2 with the respective *local scores* 0.87 and 0.93. Also, τ_6 (Figure 13) has a sub-trajectory into ROI of o_1, s_3, for which, two unusual behaviors were identified: escape with *local score* $= 0.69$ and return with *local score* $=$ 0.98.

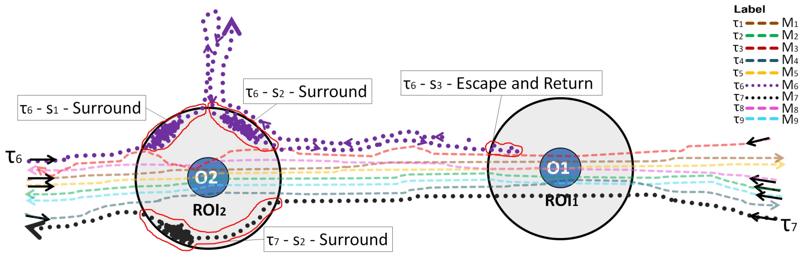

Figure 13 – Case study.

Table 2 summarizes the behaviors and local scores for M_6 after first step.

Table 2 – Step 1: Compute unusual behavior and local score of M_6.

Moving Object	Target Object	Unusual Behavior	L	w	p
M_6	o_1	Escape	0.69		
M_6	o_1	Return	0.98		
M_6	o_2	Surround	0.87		
M_6	o_2	Surround	0.93		

Following, we compute the *weight* of both target objects by analyzing the number of sub-trajectories with unusual behavior in relation to the total number of sub-trajectories that cross the region of interest.

In relation to o_1, sub-trajectory s_3 of τ_6 presents unusual behavior, sub-trajectory s_1 of τ_7 (Figure 13) does not present any unusual behavior, even though it does not cross the target object, and all the other 7 trajectories have standard sub-trajectory into ROI of both target objects. Therefore, the weight of o_1 is calculated by

$$w_{o_1} = 1 - \frac{number\ of\ \ s\ with\ unusual\ behavior}{total\ number\ \ s} = 1 - \frac{1}{9} = 0.8888 \tag{5.4}$$

where s is any sub-trajectory into ROI of o_1.

In the same way the weight of o_2 is computed. However inside the ROI of o_2, there are 3 sub-trajectories with unusual behavior: s_1 and s_2 of τ_6; and s_2 of τ_7, resulting in $w_{o_2} = 1 - 3/10 = 0.7$.

Table 3 presents the *weight* of both target objects that were computed on the second step.

Table 3 – Step 2: Compute target objects weight.

Moving Object	Target Object	Unusual Behavior	L	w	p
M_6	o_1	Escape	0.69	0.8888	
M_6	o_1	Return	0.98	0.8888	
M_6	o_2	Surround	0.87	0.7	
M_6	o_2	Surround	0.93	0.7	

The last step is calculating the percentage of unusual behavior. It is measured based on the frequency of the unusual behavior at the ROI against the total number of occurrence of the corresponding unusual behavior at the same ROI.

To compute the percentage of surround unusual behavior presented by s_1 of τ_6 we, first, have to find all sub-trajectories into ROI of o_2 that also present surround unusual behavior. Figure 13 shows that there are 3 surround unusual behaviors in relation to o_2, 2 from τ_6, s_1 and s_2, and 1 from τ_7, s_2. Given this, the surround unusual behavior percentage of s_1 at o_2 is

$$p_{\tau_6 s_1 o_2 S} = \frac{UB(o_2, "S") \in M_6}{UB(o_2, "S")} = \frac{2}{3} = 0.6667 \tag{5.5}$$

where $UB(o_2, "S")$ returns all sub-trajectories into ROI of o_2 that have the surround unusual behavior, including s_1 itself.

The same process is run for all unusual behaviors presented for every sub-trajectory into ROI of τ_6. The percentage of surround unusual behavior of s_2 ($p_{\tau_6 s_2 o_2 S}$) is 0.6667 as well as for s_1, since both are in relation to the same target object and present the same unusual behavior. The percentage of escape and return of s_3 are 1 because they are unique inside the ROI of o_1.

If we would calculate the percentage of surround unusual behavior of s_1 of τ_7 (Figure 13), we would obtain $p_{\tau_7 s_1 o_2 R} = 0.3333$ because only 1 of the 3 sub-trajectories into ROI of o_2 are from τ_7.

Finally, Table 4 shows all the values necessary to compute the global score of M_6.

Besides the local scores, weights and percentages of τ_6, we counted the total number of sub-trajectories into ROI that do not have any unusual behavior ($n = 0$) and the number of unusual behaviors ($k = 4$). So, the global score of M_6 is

Table 4 – Step 3: Compute percentage of unusual behaviors of M_6.

Moving Object	Target Object	Unusual Behavior	L	w	p
M_6	o_1	Escape	0.69	0.8888	1
M_6	o_1	Return	0.98	0.8888	1
M_6	o_2	Surround	0.87	0.7	0.6667
M_6	o_2	Surround	0.93	0.7	0.6667

$$G_{M_6O} = \frac{\left\{ + \begin{array}{c} 0.69 \times 0.88 \times 1 \\ 0.98 \times 0.88 \times 1 \\ 0.87 \times 0.7 \times 0.67 \\ 0.93 \times 0.7 \times 0.67 \end{array} \right\}}{0+4} = 0.5784 \qquad (5.6)$$

In the method proposed in this Master's thesis, after performing these 3 steps for all moving objects, the moving objects are ranked in a descendant order showing the most unusual (greatest global scores) on the top.

6 EXPERIMENTS

In order to evaluate the proposed approach we performed experiments with three different datasets of real GPS data of pedestrians, at the sampling rate of one point per second. One dataset was collected in an apartment complex in Florianópolis, Brazil. The other one is the Germania park dataset used by (ALVARES et al., 2011) for their experiments, which we use to compare our method with the Avoidance Detection. The third dataset are real trajectories of students and professors at UFSC University.

6.1 EXPERIMENT I - APARTMENT COMPLEX IN FLORIANÓPOLIS

The first dataset is a set of trajectories of 42 moving objects collected in an apartment complex in Florianópolis, considering the four monitoring areas as target objects, as shown in Figure 14. These target objects have a coverage radius of 7 meters. At any of these areas pedestrians may follow any direction or go through the main paths. This dataset was collected in order to have a ground truth. From the 42 moving objects, 5 presented unusual behaviors, and 37 had normal behavior. This dataset contains 5.125 trajectory points. The unusual behaviors were 3 surround, 2 escape, 4 return, and 7 avoidance.

After performing some experiments we defined the ROIs as 14 meters around the targets (2 times the radius of the target object), since the area is limited by the buildings. For the other parameters we used their default values, as detailed in the algorithm description ($minLength = 30\%$ of the ROI radius as the minimal length for the subtrajectory directed to the target, $\gamma_S = 3$ for the sensitivity parameter of surround, $\gamma_E = 3$ for the sensitivity parameter of escape, and $\Theta = 45°$ for the maximum angle to characterize a return behavior).

The algorithm correctly detected the 3 surround, 2 escape, 4 return, and 7 avoidance behaviors, presented in Table 5, indicating the target where each unusual behavior happened. For instance, moving object M_7, has one trajectory, τ_7, and presented three unusual behaviors: a return at o_1, and two avoidances at the same target o_1. Moving object M_{10}, for instance, had two trajectories, τ_{10} and τ_{11}, and three types of unusual behavior (surround, escape, avoidance).

Figure 15 shows the trajectories with unusual behaviors. Notice

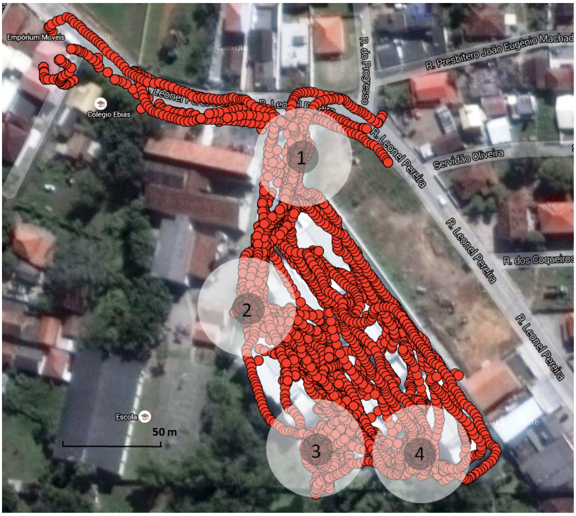

Figure 14 – Trajectories and target objects of experiment I.

that to improve the quality of visualization the trajectory points were enlarged. Figure 15 (a) shows the return behavior and two avoidance patterns at target o_1. Figure 15 (b) shows the avoidance/escape at o_1 and the surround and return at o_4 of object M_9. Figures 15 (c) and (d) show the unusual behavior of trajectories τ_{10} and τ_{11} of object M_{10}, respectively. The surround at o_3 was performed by both trajectories τ_{10} and τ_{11}. At o_2, trajectory τ_{11} performed a escape and an avoidance. When the object avoided o_2 it increased the speed of the sub-trajectory of way out. The other two avoidances of M_{10} were performed at o_3 by τ_{10} (before the surround) and by τ_{11} at o_1. Figures 15 (e) and (f) show the unusual behaviors of M_{15} and M_{17}, respectively.

Table 5 – Trajectories with unusual behavior by target object.

Moving Object	Trajectories	Surround	Escape	Return	Avoidance
M_7	τ_7			o_1	o_1, o_1
M_9	τ_9	o_4	o_1	o_4	o_1
M_{10}	τ_{10}, τ_{11}	o_3, o_3	o_2		o_1, o_2, o_3
M_{15}	τ_{15}			o_1	o_1
M_{17}	τ_{17}			o_1	

Table 6 shows the unusual behaviors of each moving object, the target where the behavior happened, and the three measures L(local

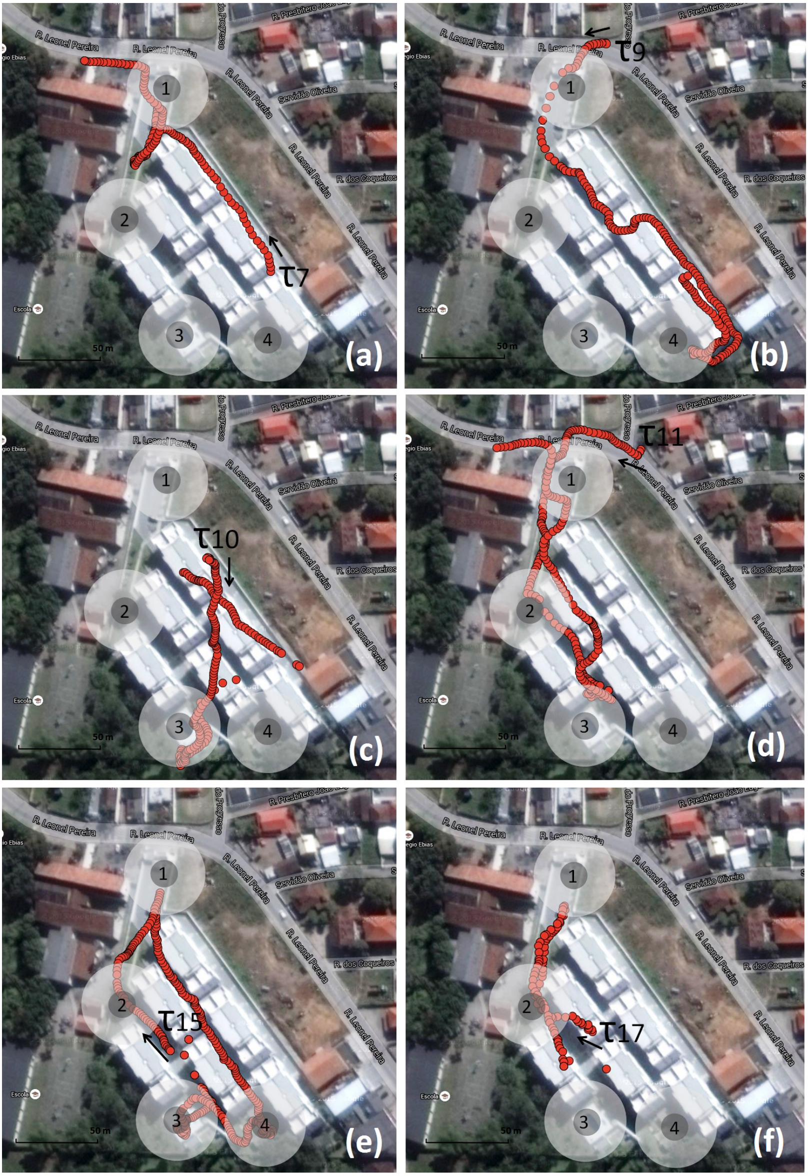

Figure 15 – Trajectories with unusual behavior.

Table 6 – Unusual behaviors detected on the apartment complex dataset.

Moving Object	Target Object	Unusual Behavior	L	w	p
M_7	o_1	Avoidance	0.5	0.75	0.4
M_7	o_1	Return	0.9963	0.75	0.3333
M_7	o_1	Avoidance	0.5	0.75	0.4
M_9	o_1	Escape	0.6148	0.75	1
M_9	o_1	Avoidance	0.5	0.75	0.2
M_9	o_4	Surround	0.8027	0.9091	1
M_9	o_4	Return	0.7911	0.9091	1
M_{10}	o_1	Avoidance	0.5	0.75	0.2
M_{10}	o_2	Escape	0.8411	0.9630	1
M_{10}	o_2	Avoidance	0.5	0.9630	1
M_{10}	o_3	Surround	0.7691	0.9167	1
M_{10}	o_3	Surround	0.7725	0.9167	1
M_{10}	o_3	Avoidance	0.5	0.9167	1
M_{15}	o_1	Return	0.9374	0.75	0.3333
M_{15}	o_1	Avoidance	0.5	0.75	0.2
M_{17}	o_1	Return	0.8933	0.75	0.3333

score), w (weight, Equation 5.4), and p (percentage, Equation 5.2) used to compute the global score.

The global score per moving object, computed according to Equation 5.3, is presented in Table 7. The first object in the ranking, with the highest global score, is M_9, followed by M_{10}. These two moving objects had more unusual behaviors and with higher values of local score, target object weight, and percentage than the other moving objects. Between them, M_{10} has lower global score mainly because the local score of all avoidance cases detected for it were the lowest possible.

Table 7 also presents a comparison of our method with the Avoidance Detection algorithm (ALVARES et al., 2011), which to the best of our knowledge is the only approach that computes trajectory unusual behavior in relation to static objects. As expected, the ranking is different, since in (ALVARES et al., 2011) only avoidance is considered, while our approach detects also surround, escape, and return behaviors.

6.2 EXPERIMENT II - GERMANIA PARK IN PORTO ALEGRE

The second experiment was performed with the dataset used in (ALVARES et al., 2011), having 17 pedestrian trajectories with 4950 points, collected at the Germania park in Porto Alegre-Brazil, conside-

Table 7 – *Ranking MOUB* (left) and Ranking of *Avoidance Detection* (right) for the apartment complex dataset.

Ranking MOUB			Avoidance Detection		
Ranking	Moving Object	Global Score	Ranking	Moving Object	Global Score
1	M_9	0.4962	1	M_{10}	0.3333
2	M_{10}	0.4036	2	M_7	0.25
3	M_7	0.1830	2	M_9	0.25
4	M_{17}	0.0744	4	M_{15}	0.125
5	M_{15}	0.0619	5	M_1	0.00
5	M_1	0.00	5	M_2	0.00
5	M_2	0.00	5	M_3	0.00
5	M_3	0.00	5	M_4	0.00
...	...	0.00	...	...	0.00

ring four target objects, as shown in (Figure 16).

Figure 16 – Trajectories and target objects of experiment II.

We run the same experiment performed in (ALVARES et al., 2011) to compare the result of *Ranking MOUB* to the result of *the Avoidance detection* algorithm, in order to show that even in a dataset generated for avoidance behavior detection, our method detects more types of unusual movements. We use the same parameters used in (ALVARES et al., 2011): 10 meters as the radius of the target object; 40 meters around the target object for the ROI; 4 meters as the minimal length for the sub-trajectory directed to the target and, as we do not have any knowledge about the region, we use the default values for the other parameters: 45° as the maximum angle for return, and 3 as the sensitivity parameter for both escape and surround.

Table 8 details all unusual behaviors detected by both methods, identifying the moving object, the target object, the type of unusual behavior, and the values to compute the global score (L, p, w). These behaviors are graphically shown in Figure 17.

The method proposed in this Master's thesis detected 4 unusual behaviors (highlighted in Table 8) that were not identified by the Avoidance Detection: one surround executed by M_7 at target o_2, one surround by M_7 at target o_3, one surround by M_8 at target o_2, and one avoidance of M_{12} at target o_3.

The avoidance executed by M_{12} can be seen in Figure 17 (d). The Avoidance Detection algorithm did not detect this avoidance because the sub-trajectory of τ_{12} in relation to o_3 crosses o_3, considering that the sub-trajectory comprehends points from the first and last point that intersect the ROI_3, even though there are points outside the ROI_3 along this path. Our algorithm correctly identifies this avoidance because two sub-trajectories into ROI_3 are considered separately. The first one has a weak avoidance, since M_{12} goes towards the target o_3, but deviates before crossing it. The second sub-trajectory into ROI_3 crosses the target, and therefore it is not an avoidance.

Table 9 presents the global score computed by both methods. The ranking is very similar, but the global scores computed by our method are lower than those computed by the Avoidance Detection. For instance, the low global score of M_8 ($GL = 0.1754$), that is mainly caused by the low weight of target object o_3 ($w = 0.5714$) and o_4 ($w = 0.06667$), and the low percentage of unusual behavior at all target object ($p = 0.5$). The weight is a degree of importance that considers the number of standard behaviors in the ROI. The lower the weight of a target object, the lower are the behaviors, because as more unusual behaviors are detected inside a ROI, less unusual they are. The percentage indicates how frequent a type of unusual behavior is at a ROI. The lower the percentage at a ROI is, less unusual is the behavior at that ROI. This occurs because when more unusual behaviors of the same type are detected for different moving objects at the same ROI, they

Table 8 – Unusual behaviors detected by *Ranking MOUB* (left) and by *Avoidance Detection* (right) on Germania park dataset.

		Ranking MOUB				Avoidance Detection	
Mov. Obj.	Tar. Obj.	Unusual Behavior	L	w	p	Unusual Behavior	L
M_4	o_4	Avoidance	0.5	0.6667	0.5	Avoidance	0.5
M_7	o_1	Avoidance	1	0.8571	1	Avoidance	1
M_7	o_2	Surround	0.6398	0.75	0.5		
M_7	o_2	Avoidance	1	0.75	0.5	Avoidance	1
M_7	o_3	Surround	0.5178	0.5714	1		
M_8	o_2	Avoidance	0.5	0.75	0.5	Avoidance	0.5
M_8	o_2	Surround	0.6319	0.75	0.5		
M_8	o_3	Avoidance	1	0.5714	0.5	Avoidance	1
M_8	o_4	Avoidance	0.5	0.6667	0.5	Avoidance	0.5
M_{12}	o_3	Avoidanc	0.5	0.5714	0.5		

represent a common behavior, and will be considered less unusual. As the weight for o_3 and o_4, and the percentage of every unusual behavior detected by M_8 per ROI are low (Table 8), the global score of M_8 is decreased, avoiding to compute false high global score for it.

Table 9 – *Ranking MOUB* (left) and Ranking of*Avoidance Detection* (right) for the Germania park dataset.

Ranking MOUB			Avoidance Detection		
Ranking	Moving Object	Global Score	Ranking	Moving Object	Global Score
1	M_7	0.4420	1	M_7	0.6667
2	M_8	0.1754	2	M_8	0.5
3	M_4	0.0833	3	M_4	0.25
4	M_{12}	0.0714	4	M_1	0.00
5	M_1	0.00	4	M_2	0.00
5	M_2	0.00	4	M_3	0.00
...	...	0.00	...	...	0.00

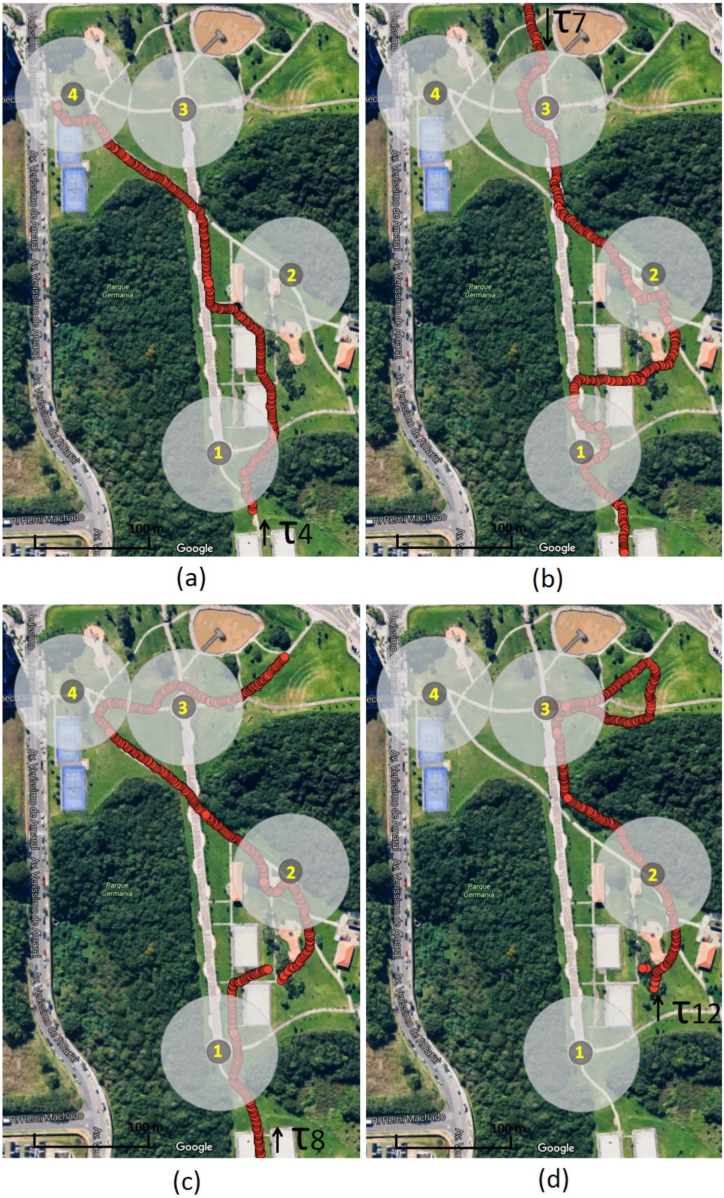

Figure 17 – Trajectories with unusual behavior.

6.3 EXPERIMENT III - FEDERAL UNIVERSITY OF SANTA CATARINA

The last dataset is a set of 823 trajectories collected at the UFSC campus by 17 students and professors in 2014, 2015 and 2016. This dataset was not generated for this Master's thesis, it is a trajectory dataset collected for general purposes. For this Master's thesis, we defined 12 target objects, including buildings, atm, bus stops, cafe, pubs and restaurants. These target objects have a coverage radius of 10 meters and a region of interest (ROI) around the target object of 20 meters, as shown in Figure 18.

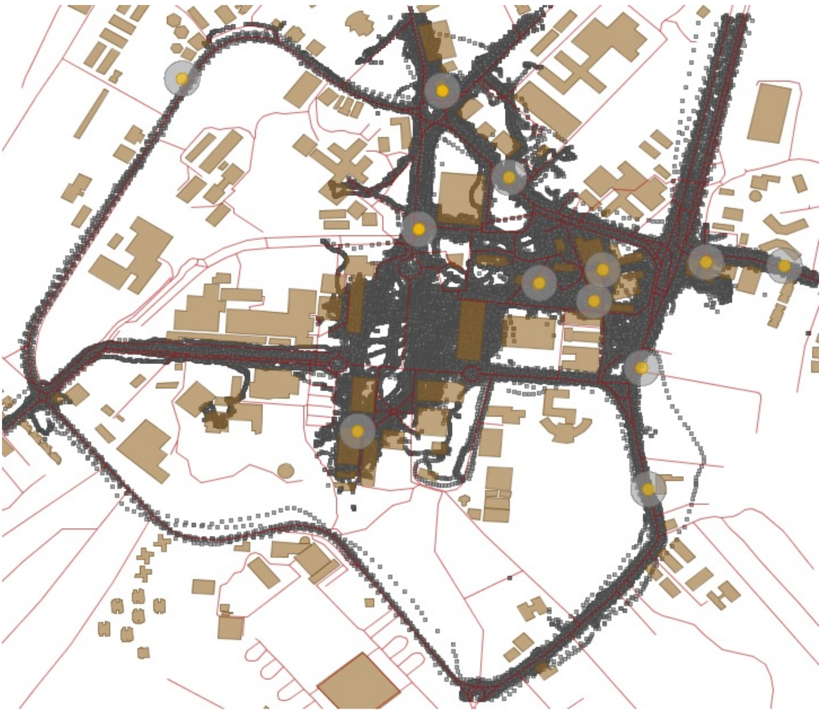

Figure 18 – Trajectories and target objects of experiment III.

As we do not know what to expect from the result of performing our method with this dataset, we simulate two moving objects with unusual behavior in relation to two target objects, in order to validate if our method correctly detects the generated unusual behaviors. We simulated one return and one avoidance at the UFSC central bus stop, and one surround around the Itaú ATM, as shown in Figure 19.

We used 5 meters as the minimal length for the sub-trajectory directed to the target. As we do not have any previous knowledge about the behaviors around the 12 target objects and there are a variety of different types of target objects, in this experiment, we use the parameter values: 45° as the maximum angle for return, and 3 as the sensitivity parameter for both escape and surround.

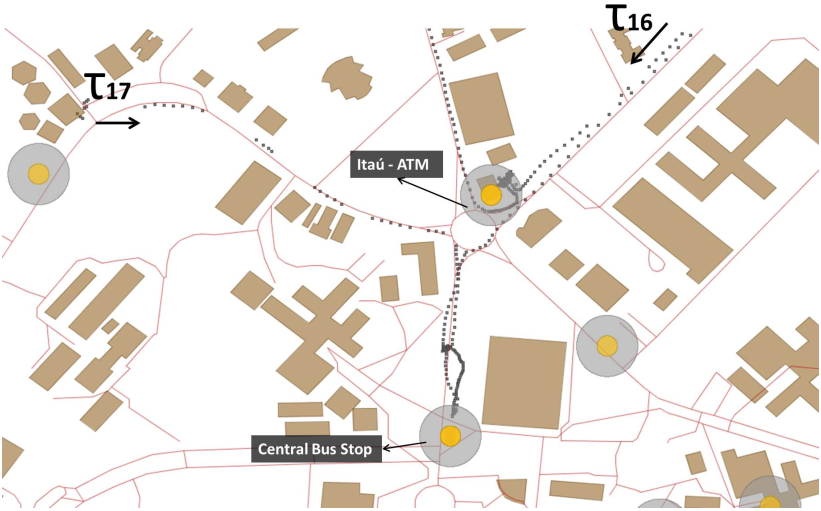

Figure 19 – Trajectories of moving objects M_{16} and M_{17}.

The method proposed in this Master's identified a large number of standard sub-trajectories at different ROIs in this dataset. The standard behavior thresholds for every single ROI are computed and presented in Table 10. A high value of the weight of a target object means that less unusual behavior occur at that target.

Based on the standard behavior thresholds of every single ROI, our algorithm detected 293 sub-trajectories with some unusual behavior among all 823 trajectories. A total amount of 367 unusual behaviors were detected: 250 were avoidance, 63 were return, only 8 were escape, and 46 were surround. Table 11 presents the ranking of students and professors moving at UFSC campus according to their global score.

As we expected, only M_{16} and M_{17} that we generated have a high global score of unusual behavior. For all other moving objects

Table 10 – Standard behavior of target object for the UFSC dataset

Target Object	Speed Threshold(m/s)	Duration Threshold(s)	Weight (w)
CTC	11.8072	1075.4389	0.8302
INE	8.2154	3262.9035	0.8930
Itaú	5.3159	54.1184	0.8980
CETEC Cafe	4.7291	754.8389	0.8427
Meu Escritorio Pub	16.1834	50.4340	0.9739
Mirantes Restaurant	95.8039	55.3765	0.9107
Restaurant	10.5096	3.0022	1
Bus Stop	10.0163	166.2464	0.9103
Bus Stop	11.6070	28.7631	0.9577
Bus Stop	13.9480	36.8134	0.9803
Central Bus Stop	9.8860	572.3543	0.9238
University Restaurant	5.2085	1672.0368	0.7277

global scores were very low, even though they presented some kind of unusual behavior. This is because among all trajectories of such moving objects, there are much more sub-trajectories with standard behavior than sub-trajectories with unusual behavior. This means that the moving object presents standard behavior in general. For instance, for M_{13}, 31 unusual behaviors were detected in 22 sub-trajectories in relation to 6 different target objects, in a total of its 72 sub-trajectories identified inside the ROIs. Table 12 details the unusual behaviors detected for the first three moving objects of the ranking (M_{13}, M_{16} and M_{17}), identifying the moving object, the target object, the type of unusual behavior, and the values to compute the global score.

Through the analysis of Table 12 we can understand why M_{13} has a very low global score, even though it has 31 unusual behaviors. The 12 avoidances highlighted in Table 12 were detected in relation to target objects where avoidance is a common behavior ($p = 0.0762$, $p = 0.0717$, $p = 0.083$, $p = 0.022$). Avoidance at INE is a normal behavior because students and professors arriving at UFSC campus, usually

Table 11 – *Ranking MOUB* for the UFSC dataset.

Ranking	Moving Object	Global Score
1	M_{16}	0.4757
2	M_{17}	0.2450
3	M_{13}	0.0506
4	M_3	0.048
5	M_4	0.0447
6	M_5	0.0445
7	M_7	0.0412
8	M_{11}	0.0301
9	M_1	0.0299
10	M_{15}	0.0235
11	M_8	0.0166
12	M_{14}	0.0121
13	M_2	0.0113
14	M_9	0.0022
15	M_{10}	0.0012
16	M_6	0.0007
17	M_{12}	0

park their cars around INE, so they move towards INE, changing their direction and deviating from INE to park, causing an avoidance that is not unusual, but very common. But this is not a problem since the percentage parameter will reflect this, having a very low value, what means that these avoidances are not so important. In addition, low local scores around 0.5 (underscored in Table 12) were computed for 18 of the 31 unusual behaviors. Most trajectories of this dataset behave like M_{13}, what explains why they have very low global scores even though they have several unusual behaviors.

On the contrary, moving objects, M_{16} and M_{17} present unusual behavior in relation to every single ROI they go through and the global scores computed for them are much higher than the average overall of all moving objects. Therefore they can be considered unusual in general.

For M_{16}, the two simulated behaviors in relation to the Itaú ATM were correctly detected by our method: a surround with 0.9877 of local score, which is unique ($p = 1$); and an avoidance with 1 of local score, but this avoidance was also detected for other 13 sub-trajectories from other moving objects, which means it is a bit common at the ROI ($p = 0.0714$), causing a decrease on M_{16} global score. For M_{17}, two unusual behaviors in relation to the UFSC central bus stop were detected: a return with 0.7332 of local score, which is unique; and an avoidance with 0.5 of local score, that was detected for other 7 sub-trajectories from other moving objects, that also decreases the global score of M_{17}. Besides, both of them do not present standard behavior in relation to any other target object.

So, after performing the experiment with the UFSC trajectories dataset, we can say that our method detects and ranks moving objects according to the unusual behaviors identified on their trajectories in relation to target objects for any region.

6.4 DISCUSSION

The results of the proposed method, as for most methods for trajectory data analysis, can be influenced by data imprecision and noise. To minimize this problem, a preprocessing step to the input trajectories is recommended.

The parameter values can affect the results of the method, and should be defined taking into account the specific application and the environment. The size of the ROI around the target object, for instance, should be defined considering the features of the target object and the environment. If the environment is an open area like a park, the size of the ROI can be larger than if the target is located in a region with many buildings that occlude the vision and the movement. The idea is that the ROI should be large enough such that an unusual behavior can be detected, and not too large to avoid that a movement independent from the target could be interpreted as an unusual behavior related to the target.

The intuition of the parameter minimal length of the sub-trajectory directed to the target to identify an avoidance pattern is to ensure that the moving object was really going towards the target. The default value for this parameter is 30% of the radius of the ROI around the target.

The parameters sensitivity for surround and escape will define the number of unusual behaviors to be detected. The default value is 3 standard deviations, which is normally used in statistics to find outliers. This value can be changed in order to detect more or less escape and surround behavior. The higher this value is, the stronger and more important will the unusual behaviors be.

The maximum angle to characterize a return behavior has a default value of 45 degrees, which is already restrict. This parameter should not be higher than 90 degrees, since the larger this value is, the higher will be the number of *returns* that can be detected when a moving object simply turns a corner.

The characteristics of the input trajectories are also very important. For instance, trajectories of pedestrians with points collected at intervals of around 30 seconds are not suitable to analyze the proposed unusual behaviors, since more detailed movement tracks are needed.

An important remark is that the main use of the proposed unusual behaviors is to rank the moving objects according to their degrees of unusual movement. In general, there will be a reasonable long trajectory of each moving object, or several trajectories. With these conditions, a few false positives or false negatives will not affect the final results, since , in average a normal moving object will have a much lower *global score* than a suspicious individual, although the global score for most moving objects will be greater than zero.

Table 12 – Unusual behaviors detected by *Ranking MOUB* for the first three moving objects of the ranking.

Mov. Obj.	Target Object	Unusual Behavior	L	p	w
M_{13}	CTC	2 x Avoidance	$1, \underline{0.5}$	0.1	0.8302
M_{13}	CTC	3 x Return	0.7697, 0.9725, 0.9653	0.4286	0.8302
M_{13}	INE	8 x Avoidance	$\underline{8 \text{ x } 0.5}$	0.0762	0.8930
M_{13}	INE	8 x Return	$\underline{0.5}$, $\underline{0.5835}$, 0.8477, 0.7824, 0.94, 0.9863, 0.9474, 0.9148	0.25	0.8930
M_{13}	Itaú	Avoidance	$\underline{0.5}$	0.0714	0.898
M_{13}	CETEC Cafe	2 x Avoidance	$\underline{2 \text{ x } 0.5}$	0.083	0.8427
M_{13}	CETEC Cafe	Return	0.8554	0.25	0.8427
M_{13}	Bus Stop	Avoidance	1	0.33	0.9577
M_{13}	Central Bus Stop	2 x Avoidance	$\underline{2 \text{ x } 0.5}$	0.25	0.9238
M_{13}	University Restaurant	Avoidance	$\underline{0.5}$	0.022	0.7277
M_{13}	University Restaurant	Return	0.9048	0.0714	0.7277
M_{13}	University Restaurant	Surround	$\underline{0.5478}$	0.0714	0.7277
M_{16}	Itaú	Avoidance	1	0.0714	0.8973
M_{16}	Itaú	Surround	0.9877	1	0.8973
M_{17}	Central Bus Stop	Avoidance	0.5	0.125	0.9238
M_{17}	Central Bus Stop	Return	0.7332	1	0.9238

7 CONCLUSION AND FUTURE WORK

In this Master's thesis we define three new types of unusual behaviors that a moving object may have in relation to static areas or objects: surround, escape and return.

We proposed the general concept of unusual behavior, that represents movement with different characteristics from the standard behavior observed at each target object. The proposed method dynamically computes the standard (normal) behavior at every single target object. However for this, it demands that, at least, one moving object crosses the target object.

We defined measures to compute the local score and the global score of unusual movements. Local score is a degree of unusual behavior of a moving object in relation to a single target object. Global score is a degree of unusual behavior of a moving object in relation to all target objects it passes nearby, taking into account the local scores, the recurrence of unusual behaviors, and the weight of each target object.

We proposed an algorithm that computes unusual behaviors and ranks moving objects accordingly. The proposed approach was evaluated with three experiments with GPS trajectories, among which one was generated to validate the method, one was generated to validate only avoidance behaviors in (ALVARES et al., 2011) and another used every day real movements, where users were not aware about the experiments.

We submitted a paper to International Journal of Geographical Information Science, which was published on 27/06/2016.

Future ongoing work includes the use of semantic information of moving objects and target objects to better interpret the unusual behaviors. Indeed, we will investigate if more information about the moving objects, such as transportation means, can be useful to detect unusual behavior. Another future extension can be achieved through a further analysis of trajectories that cross the target object, in order to identify the moving objects that present different behavior from the standard behavior of the region, mainly escape cases, also ranking them according to their unusual behavior. Another interesting improvement would be removing or decreasing the importance level of target objects that few people cross through or we should dynamically detect that do not cross is the standard behavior.

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